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Optimised spatial planning to meet long term urban sustainability objectives

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ABSTRACT

Urbanisation, environmental risks and resource scarcity are but three of many challenges that cities must address if they are to become more sustainable. However, the policies and spatial development strategies implemented to achieve individual sustainability objectives frequently interact and conflict presenting decision-makers a multi-objective spatial optimisation problem. This work presents a developed spatial optimisation framework which optimises the location of future residential development against several sustainability objectives. The framework is applied to a case study over Middlesbrough in the North East of the United Kingdom. In this context, the framework optimises five sustainability objectives from our case study site: (i) minimising risk from heat waves, (ii) minimising the risk from flood events, (iii) minimising travel costs to minimise transport emissions, (iv) minimising the expansion of urban sprawl and (v) preventing development on green-spaces. A series of optimised spatial configurations of future development strategies are presented. The results compare strategies that are optimal against individual, pairs and multiple sustainability objectives, such that each of these optimal strategies out-performs all other development strategies in at least one sustainability objective. Moreover, the resulting spatial strategies significantly outperform the current local authority strategy for all objectives with, for example, a relative improvement of up to 68% in the performance of distance to CBD. Based on these results, it suggests that spatial optimisation can provide a powerful decision support tool to help planners to identify spatial development strategies that satisfy multiple sustainability objectives.

1. Introduction

Urban planning is being challenged by multiple drivers, including rising populations, increased frequency of extreme events and actions to decarbonise economies to mitigate against a changing climate. By 2030 it is estimated that 60% of the world's population will reside in urban areas, up from just over 50% at present (UNFPA (United Nations Population Fund), 2011). This increased urban population will increase risks to natural hazards over the next century and these will be compounded by extreme events that are expected to increase in frequency as a result of changes in sea level, precipitation, temperature and other climate phenomena (Dawson, 2007; Hunt & Watkiss, 2011; IPCC (International Panel on Climate Change), 2013). However, urban areas are major drivers of climate change, directly or indirectly producing 71% of global carbon emissions (IEA (International Energy Agency), 2008) and are seen as 'first responders' at reducing energy and resource usage to mitigate further climatic change (Reckien et al., 2014; Rosenzweig, Solecki, Hammer, & Mehrotra, 2010).

Addressing these drivers of change, and other issues of sustainability more generally, has potential to lead to conflicts and trade-offs as even well intended interventions in one sector can have undesirable impacts on other sectors (Dawson, 2011; Mcevoy, Lindley, & Handley, 2006). For example in the last decade the paradigm for spatial planning policy in Europe has focused almost exclusively on mitigation of GHG emissions through urban intensification (Biesbroek et al., 2010) as denser cities are typically associated with lower transport energy use (Newman & Kenworthy, 1989; Williams, Burton, & Jenks, 2000). However urban intensification has been found to exacerbate urban heat islands, increase flood risk by reducing surface permeability and lead to poor health outcomes for residents (Dawson, 2007; Holderness, Barr, Dawson, & Hall, 2013; Hunt & Watkiss, 2011; Melia, Parkhurst, & Barton, 2012). Furthermore, analysis by Echenique, Hargreaves, Mitchell, and Namdeo (2012) suggest that compact city development results in only minor reductions in travel distances and that these benefits were often outweighed by loss of housing choice, increased crowding and congestion. It is therefore essential that spatial planners avoid making assumptions about the relative merits of compaction and dispersion, and consider evidence about the performance of multiple sustainability objectives, over short and longer timeframes (Campell, 1996; Dawson, 2011).

In the UK, and many other countries, sustainability appraisals within the planning process typically consider these issues in a highly subjective manner with little analytical consideration of the evidence,

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trade-offs and potential synergies between objectives (Gibson, 2006). Traditionally spatial planning decisions have been taken on the basis of 'satisficing' (Simon, 1996) i.e. selecting plans which exceed an acceptability threshold for planning objectives. However, there is a growing body of work that has demonstrated the effectiveness of spatial optimisation techniques to plan infrastructure, such as water distribution networks (Fu, Kapelan, Kasprzyk, Reed, & Asce, 2013; Keedwell & Khu, 2005; Prasad & Park, 2004; Vamvakeridou-Lyroudia, Walters, & Savic, 2005), and transport networks (Bielli, Massimiliano, & Carotenuto, 2002; Delme, Li, & Murray, 2012; Shimamoto, Murayama, Fujiwara, & Zhang, 2010) as well as within land use planning applications (Balling, Taber, Brown, & Day, 1999; Liu et al., 2015; Loonen, Heuberger, & Kuijpers-Linde, 2007; Stewart & Janssen, 2014). Indeed at the scale on entire urban systems, spatial optimisation has been employed to successfully maximise land use compatibility (Cao et al., 2011; Khalili-Damghani, Aminzadeh-Goharrizi, Rastegar, & Aminzadeh-Goharrizi, 2014; Ligmann-zielinska et al., 2005) and in design spatially optimal compact cities (Ligmann-zielinska, Church, & Jankowski, 2005).

Over several decades a number of optimisation algorithms have been adapted and developed for use in the spatial design and planning of infrastructure and urban systems, ranging from the use of relatively simple approaches such as gradient-based and Tabu local search methods (Costamagna, Fanni, & Giacinto, 1998; Jaeggi, Parks, Kipouros, & Clarkson, 2008), through to more complex approaches such as genetic algorithms, which mimic evolutionary operators over a set of solutions to search for optimal solutions to a problem (Konak, Coit, & Smith, 2006; Xiao 2008), particle swarm optimisation which guides a series of solutions through the variable space mimicking the way organisms naturally swarm (Coello, Pulido, & Lechuga, 2004; Poli, Kennedy, & Blackwell, 2007) and ant colony optimisation, which identifies best paths to optimal solutions (Dorigo & Blum, 2005; Yu, Yang, & Xie, 2011); approaches that have been applied to land use allocation studies (Aerts, Eisinger, Heuvelink, & Stewart, 2003; Arthur & Nalle, 1997; Cao, Huang, Wang, & Hui, 2012; Chuvieco, 1993; Liu, Li, Shi, Huang, & Liu, 2012; Liu et al., 2015; Masoomi, Mesgari & Hamrah, 2013; Qian, Pu, Zhu, & Weng, 2010; Stewart, Janssen & Herwijnen, 2004).

However, to date the use of spatial optimisation to tackle multiple real world sustainability objectives from a broad spectrum of long-term sustainability issues (risk prevention, mitigation of transport emissions etc.) in applications that closely resemble the planning decisions faced in the future with regard to sustainable development of urban systems has been somewhat limited (Keirstead & Shah, 2013). Indeed previous research has primarily focused on obtaining optimal land use allocations (Cao et al., 2012; Qian et al., 2010), but in the absence of an appreciation of real-world risks faced by urban systems in the future, such as climate change induced heat and flood hazards (Reckien et al., 2014).

To address this sparsity in the evaluation of multiple real world sustainability objectives within the spatial planning of new development this work develops a spatial optimisation framework based around resource allocation; an approach that complements the 'evolutionary' approach 'to planning sustainable urban areas' (Ligmann-zielinska et al., 2005). The framework is novel in that it couples simulated annealing, an approach that has been found to be computationally efficient for high-dimensional spatial optimisation problems (Duh & Brown, 2007) and a proven ability in resource applications (Aerts & Heuvelink, 2002; Sidiropoulos & Fotakis, 2009), with Pareto-optimisation (Xiao, Bennett, & Armstrong, 2007), such that comparisons can be undertaken rapidly and in a straight forward manner between the optimal spatial solutions found for different combinations of multiple sustainability objectives. A case study, applied to Middlesbrough Borough Council a local authority area in the North East of England (Fig. 1), demonstrates how spatial Pareto-optimisation based on a simulated annealing framework (Kirkpatrick, Gelatt, & Vecchi, 1983) can be employed to derive spatial development patterns that are sensitive to climate induced hazards such as heat and flood whilst accounting for current planning policies that seek to avoid fragmented urban growth and development on green space. This multi-objective spatial Pareto-optimisation approach comprises three main steps:

(i) Define the set of sustainability objectives that are to be optimised within the framework (Section 2.1);
(ii) Apply a simulated annealing algorithm to generate spatial configurations of new development that meet the sustainability objectives (Section 2.2);
(iii) Use a sorting procedure to extract the Pareto-optimal sub-set of solutions that perform better than all tested solutions in at least one of the sustainability objective outlined (Section 2.3).

Section 3 presents the results of a case study in Middlesbrough in the UK, identifying optimal locations of development before outlining the

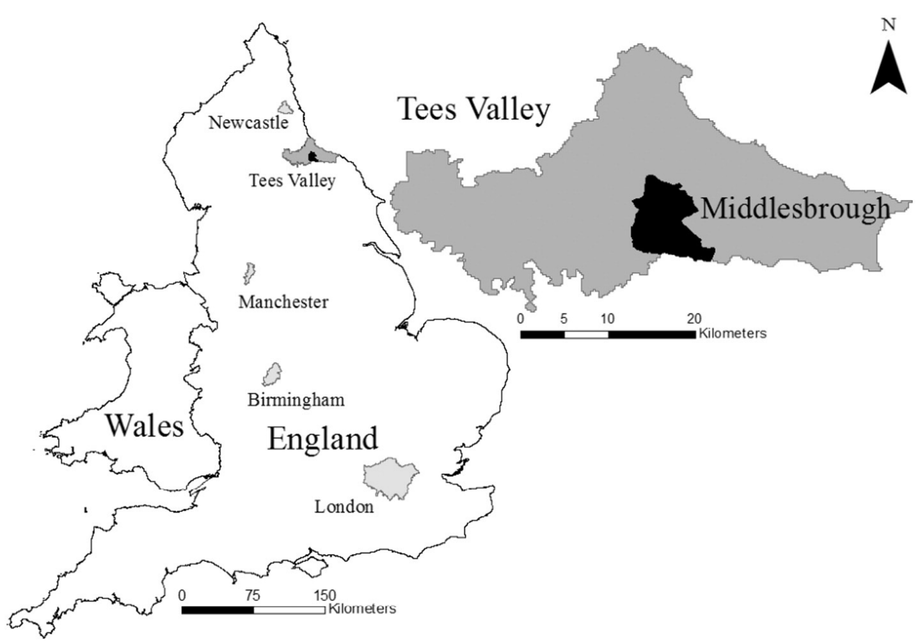

Fig. 1. The case study area of Middlesbrough within the Tees Valley.

main conclusions and implications of the work. Lastly Section 4 concludes the paper and summarises the findings.

2. Methodology

2.1. Selection and parameterisation of sustainability objectives

An extensive review was undertaken of the spatial planning and urban sustainability academic literature (for example Melia et al., 2012, Carter, 2011; Hunt & Watkiss, 2011), sustainability appraisals and the approaches employed for development plans within the UK (including DCLG (Department for Communities and Local Government), 2008 and GLA (Greater London Authority), 2011) and internationally (including American Planning Association, 2000 and City of Sydney, 2011). From this review, five sustainability objectives were selected on the basis that they (i) they were frequently used, (ii) covered a wide range of sustainability issues, including risk prevention as well as typical energy mitigation objectives, and (iii) data was available for spatial parameterisation within the optimisation framework. The selected objectives are:

1. **Minimising risk from future heat waves:** Policy appeared in 40% of sustainability appraisals reviewed, and is prioritised by national governments, including the UK (Defra, 2012).
2. **Minimising the risk from future flood events:** Avoiding appropriating new development in areas that are at risk of future flooding was highly prioritised by 70% of sustainability appraisals reviewed and a priority policy for the UK government (Defra (Department for Environment, Flood and Rural Affairs), 2010).
3. **Minimise travel costs to minimise transport emissions:** All sustainability appraisals reviewed stated this as a high priority sustainability objective, which in turn reflects the high priority of mitigating emissions from private transports (GLA (Greater London Authority), 2011).
4. **Minimise the expansion of urban sprawl:** Expansion of urban limits has been found to increase travel costs and its prevention is a national priority through policies encouraging development of previously developed sites within existing urban areas (DCLG, 2012).
5. **Preventing development of green-space:** Appears as a sustainability objective in 80% of sustainability appraisals reviewed, which include the protection of biodiversity and urban greening.

Fig. 2 presents the input raster datasets for the parameterisation of the sustainability objectives outlined which are at a 100 metre spatial resolution and were pre-processed using the ArcMap 10.1 software package. Objective 1 is achieved by preventing high densities of population in areas expected to have high incidences of heat waves in the future. The framework intends to minimise the objective function f_{heat} characterised by the increase in heat risk in the future relative to the baseline date:

$$\text{Minimise } f_{heat} = \sum H_{ij}^{Future} - \sum H_{ij}^{Current}$$

where H_{ij}^{Future} and $H_{ij}^{Current}$ are defined as being the cross product of the probability of a heat hazard event (h_{ij}) occurring at a particular location (i,j) and its corresponding population vulnerability,v_{ij}, expressed in terms of population density (people per-hectare). As development sites, d_{ij}, are assigned spatially, the calculation of H_{ij}^{Future} is updated at each iteration of the optimisation to account for the new calculation of v_{ij} due to the increase in population density associated with the spatial arrangement of $d_{ij} \in D$, where D is a collection of d_{ij} constituting a development plan. Heat hazard, h_{ij}, in Fig. 2a was sourced from spatially disaggregated 2020 heat wave frequency projections using medium emission UKCP09 climate projections (Jones, Kilsby, Harpham, Glenis, & Burton, 2009), whilst vulnerability, v_{ij}, in Fig. 2b was

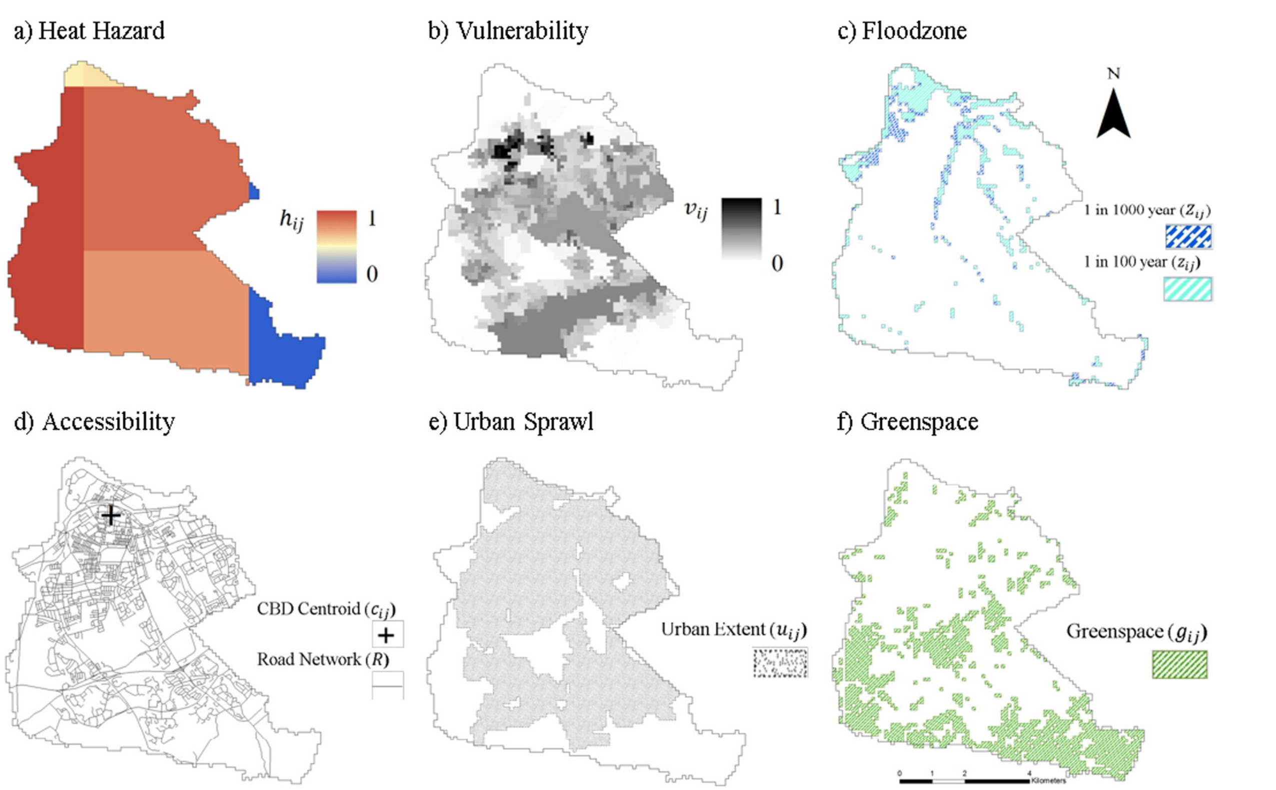

Fig. 2. Input datasets for the parameterisation of sustainability objectives.

represented by population density (per-hectare) derived from England and Wales (UK) 2011 census data (ONS (Office of National Statistics), 2012) at the lower super output area level (a spatially variable census zonal geography that represents on average 309 people). Objective 2 was optimised on the basis of minimising the objective function f_{flood} which is characterised by a proportional risk assessment of development within 1 in 100 and 1 in 1000 year flood zones represented as:

$$\text{Minimise} \quad f_{flood} = 10^0 \sum (d_{ij} = Z_{ij}) + 10^{-1} \sum (d_{ij} = z_{ij})$$

where Z and z are spatial grids representing 1 in 100 and 1 in 1000 flood zone extents respectively. Flood zones shown in Fig. 2c were sourced from the UK's Environmental Agency's (EA) Flood zone maps. Objective 3 was realised through optimising an accessibility measure to areas of employment and services, namely distance of new development to the current Central Business District (CBD) with the reduction of commuting acting as a proxy for reducing transport emissions. An accessibility measure is used as they have been reported to be more strongly related to vehicle miles travelled than other measures such as compaction (Ewing & Cervero, 2010). The optimisation attempts to minimise the objective function f_{dist} which is expressed by the average shortest path, $P(\ )$, between proposed development sites, d_{ij}, and a point designated as a CBD centroid, c_{ij}, over a road network, R:

$$\text{Minimise} \quad f_{dist} = Min(P(d_{ij}, c_{ij}, R) \forall c_{ij} \wedge d_{ij} \in D).$$

Middlesbrough's CBD, c_{ij}, was represented by centroid of Town Centre Boundary as defined by Middlesbrough Council's Local Development Framework whilst the road network was represented by all major roads in the Ordnance Survey (the UK's national mapping agency) Meridian 2 dataset (Fig. 2d). Objective 4 was optimised on the basis of ensuring that new development is within existing urban borders, u_{ij}, and characterised by the objective function f_{sprawl}:

$$\text{Minimise} \quad f_{sprawl} = \sum d_{ij} \neq u_{ij} \forall d_{ij} \in D.$$

The current urban extent, Fig. 2e, was extracted and rasterised from Ordnance Survey Meridian 2 Developed Land Use Areas (DLUA). Lastly objective 5 was achieved through imposition of a spatial constraint on the selection of solutions in the form of $d_{ij} \neq g_{ij} \forall d_{ij} \in D$, where g_j are the spatial locations (cells) of green space (see Fig. 2f). Greenspace in Middlesbrough, g_{ij}, was extracted from Ordnance Survey MasterMap topographic data with Natural theme.

2.2. Simulated annealing approach to spatial optimisation

Simulated annealing is a probability approach that intelligently searches iteratively for optimal solutions for a particular acceptance criteria (Kirkpatrick et al., 1983). It has been used for several spatial optimisation problems, including resource allocation, (Aerts & Heuvelink, 2002), ground water allocation (Sidiropoulos & Fotakis, 2009) and spatial allocation (Duh & Brown, 2007). Fig. 3 shows the structural components of the simulated annealing algorithm used in this study to simultaneously optimise the outlined objectives and generate the list of potentially optimal solutions (S_b). The procedure begins with an assumed initial spatial configuration of new development, D (in this example the current development plan, Fig. 4a, is used). Each configuration, D_n, is evaluated against the objective functions outlined in the previous sections to give associated performance scores, f_n (which comprises $f_{heat}, f_{flood}, f_{dist}, f_{sprawl}$) and the best score at the n^{th} simulation, f_b. To generate a new spatial development configuration, D_{n+1}, an existing development site $d_{ij} \in D_n$ is moved randomly within an 8-cell Moore neighbourhood. All superior solutions, D_b, are added to the solution

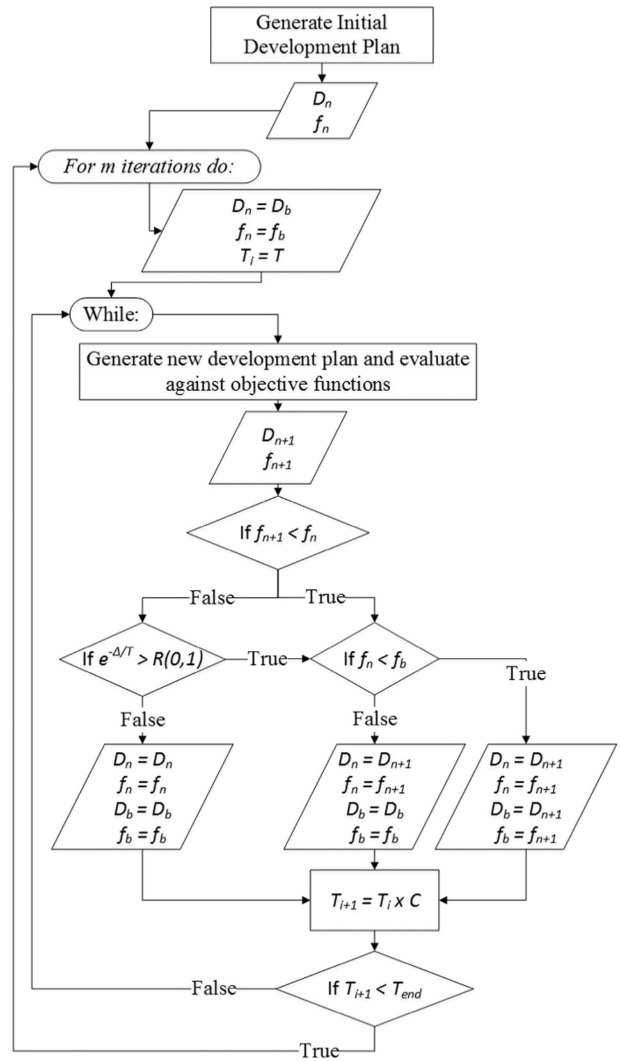

Fig. 3. Flow diagram of the simulated annealing approach to spatial optimisation.

list, S_b, but inferior solutions can be accepted on the basis of the Thermopolis equation:

$$e^{-\Delta/T} > R(0,1) \tag{1}$$

where Δ is the difference between f_n and f_{n+1}, whilst $\mathbb{R}$ represents a real number between 0 and 1. This prevents the algorithm converging on local optima by encouraging the evaluation of a wide range of spatial development patterns. At the end of each iteration the temperature variable, T, is decreased by a cooling factor C:

$$T_{i+1} = T_i \times C \tag{2}$$

where $0<C<1$ (in many simulated annealing applications C is set between 0.8 and 0.98 (Aerts & Heuvelink, 2002)). As T decreases, Eq. (1) restricts the acceptance of solutions to help convergence on a global optimal solution across the entire range of possible spatial development patterns. The algorithm is repeated until T T_{end}, and this process is then repeated for a user defined number of iterations, m. Throughout the operation a best performing development pattern and associated performance score is retained as D_b, f_b which replaces D_n and f_n at the start of each iteration. This aids convergence to a globally optimum best performing spatial configuration as the algorithm can move from an already known optimal spatial layout. For the application

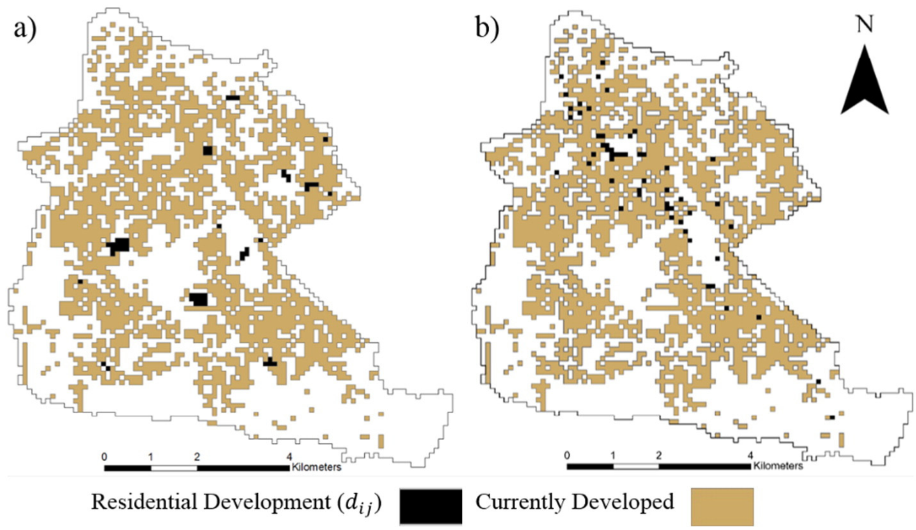

Fig. 4. a) Middlesbrough Council's own development plan (Middlesbrough Council, 2013) and b) optimised spatial plan of residential development found by the simulated annealing algorithm.

the framework was run with the following parameters: $T = 1.0^{100}$, $T_{end} = 0.01$, $C = 0.85$ and $m = 150$, and took 5 h and 12 min to run.

Fig. 4 demonstrates the best performing optimised spatial plan based on normalised objective functions (b) compared with Middleborough Councils' own development plan (a); in this case the spatial optimised solution performed better in all 4 objectives than the council plan (for instance reducing f_{sprawl} from 29.6 to 13.0).

2.3. Pareto-optimal extraction

Once S_b has been populated with an extensive and diverse collection of configurations ($s \in S_b$), a non-dominated sorting based on Mishra and Harit (2010) was applied to extract the set of Pareto-optimal solutions; an approach that has been used extensively in the engineering optimisation, including water distribution systems (Fu et al., 2013; Vamvakeridou-Lyroudia et al., 2005) land use allocation (Cao et al., 2011; Jiang-Ping & Qun, 2009) and risk mapping (Woodward, Kapelan, & Gouldby, 2013). The strength of this approach is that it provides planners with a wide choice of known best trade-off solutions to choose from, as opposed to a single optimal solution based on a set of pre-defined priorities or weights (Jiang-Ping & Qun, 2009). This has the advantage that the results are independent of any prior subjective preferences which have the potential to be error prone and lead to erroneous conclusions. Rather, the Pareto-optimal results provide optimal quantitatively characterised result-set vectors from which particular solutions can be objectively selected (Deb, 2001).

For a set of objective functions, F, S_b is sorted according to the first objective function, $f_1 \in F$. The top solution is popped and recorded in a non-dominated list, N. Pareto-optimal solutions are determined based on the concept of domination. For F objective functions a solution $s^{(1)}$ is said to dominate solution $s^{(2)}$ if:

1. The solution $s^{(1)}$ is no worse than $s^{(2)}$ in all objectives; $f(s^{(1)}) \le f(s^{(2)}) \,\forall f \in F$;
2. The solution $s^{(1)}$ is strictly better than $s^{(2)}$ in at least one objective; $f(s^{(1)}) < f(s^{(2)})$ for at least one $f \in F$ (Deb, 2001).

If a solution, s^n, is found to be non-dominated by all solutions in the non-dominated list $p \in N$, it is added to the list. Moreover, if the solution is found to dominate any $p \in N$, the dominated element of N is removed. To ensure computational efficiency the procedure is initiated using the most probable non-dominated solution so that dominated solutions are realised quicker (Mishra & Harit, 2010). Here, Pareto-optimal spatial configurations are those where no other spatial configuration performs better with regard to a combination of f_{risk}, f_{flood}, f_{sprawl} and/or f_{dist}. Several sets of N were derived. The first set contains multi-objective Pareto-optimal (MOPO) solutions where $F = \{f_{heat}, f_{flood}, f_{dist}, f_{sprawl}\}$, to identify the best overall set of trade-off configurations that can be achieved. Further sets of Pareto-optimal spatial configurations were extracted for different sub-sets of sustainability objectives in order to demonstrate trade-offs between each combination of pairs of objectives:

$$\text{E.g.} \left\{ f_{heat}, f_{flood} \right\} \subseteq F, \{ f_{heat}, f_{dist} \} \subseteq F \ldots$$

where, for the example set of $\{f_{heat}, f_{flood}\}$, all the solutions contained within it outperform all other found solutions in at either f_{heat} or f_{dist} or both. The entire framework was developed using the Python scripting language whilst the results are visualised in ArcMap 10.1.

3. Results and discussion

3.1. Pareto-optimal fronts between pairwise sustainability objectives

Fig. 5 presents the results of the optimisation framework and shows the normalised performances of Pareto-optimal fronts and the sub-set of solutions that are optimal for multiple sustainability objectives (MOPO). The performance of the current development plan (Middlesbrough Council, 2013) is highlighted for comparison. Table 1 summarises the statistical properties of each Pareto front, whilst Table 2 compares the performance of the current development proposal against optimised solutions, demonstrating the far superior performances for sustainability objectives achieved by the Pareto-optimal spatial configurations. For each objective the optimisation algorithm is able to find many strategies that improve upon each objective against the current development plan; the current development plan is outperformed by 85% of solutions found by the framework in f_{heat}, 68% in f_{dist} and 88% in f_{sprawl}. Notably, the algorithm is also able to identify strategies that improve upon the current plan across all sustainability objectives including a 6% reduction in f_{heat} and 37% reduction in f_{dist}, whilst not adding further flood risk or encroaching upon green space. Our results suggest that there is potential to significantly improve upon the current plan in the context of these sustainability objectives.

The results demonstrate that there is a clear conflict between f_{heat} and both f_{dist} and f_{sprawl} whilst planning new residential development in Middlesbrough. The best performance for f_{heat}, min (f_{heat})$\in S_b$,

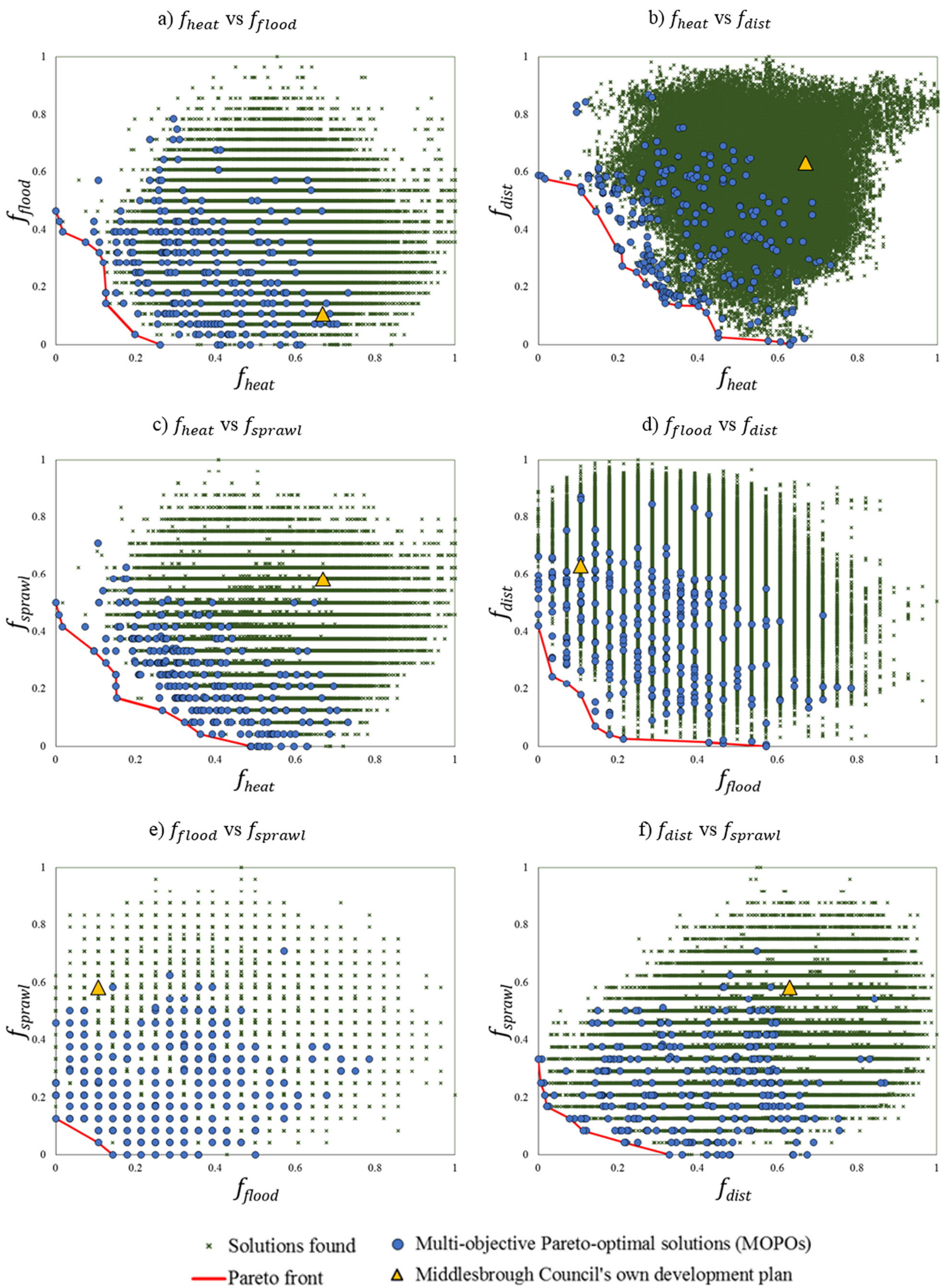

Fig. 5. Pareto-optimal solutions between sustainability objectives.

Table 1
Pareto-front statistics.

	Conflict	No. of pairwise Pareto-optimal	Min ()	Min (normalised)	Max	Median
55a	f_{heat} v	10	f_{heat}	3574.9 (0)	3737.6 (0.26)	3642.4 (0.11)
	f_{flood}		f_{flood}	0 (0)	416 (0.46)	288 (0.32)
55b	f_{heat} v	23	f_{heat}	3574.9 (0)	3967.9 (0.63)	3742.9 (0.27)
	f_{dist}		f_{dist}	2900.5 (0)	4556.6 (0.59)	3487.7 (0.2)
55c	f_{heat} v	12	f_{heat}	3574.9 (0)	3879.3 (0.49)	3668.8 (0.15)
	f_{sprawl}		f_{sprawl}	3.7 (0)	25.9 (0.5)	14.81 (0.25)
55d	f_{flood} v	10	f_{flood}	0 (0)	512 (0.57)	128 (0.14)
	f_{dist}		f_{dist}	2900.5 (0)	4084.2 (0.42)	3096.7 (0.01)
55e	f_{flood} v	3	f_{flood}	0 (0)	128 (0.14)	96 (0.11)
	f_{sprawl}		f_{sprawl}	(0)	9.3 (0.13)	5.5 (0.04)
55f	f_{dist} v	8	f_{dist}	2900.5 (0)	3827.6 (0.33)	2960.9 (0.02)
	f_{sprawl}		f_{sprawl}	0 (0)	18.5 (0.33)	11.1 (0.17)

comes at a compromise of a normalised value of 0.59 for f_{dist} and 0.5 for f_{sprawl}. Whilst $\min(f_{dist}) \in S_b$ and $\min\ (f_{sprawl}) \in S_b$ come at a compromise for f_{heat} with normalised values of 0.63 and 0.49 respectively. The conflict occurs because areas close to the CBD and within the current urban extent have higher population densities, which in turn lead to higher heat risk. As the CBD is located within the urban extent it is perhaps surprising that our analysis highlight a conflict between f_{dist} and f_{sprawl}, with $f_{sprawl} = 0.33$ for $\min(f_{dist}) \in S_b$ whilst $f_{dist} = 0.33$ for $\min\ (f_{sprawl}) \in S_b$. This is caused by the spatial layout of Middlesbrough, where there are undeveloped areas west of the CBD which are not within the current urban extent. As a result of these conflicts there are numerous Pareto-optimal solutions found between these pairs of sustainability objectives with an outstretched Pareto front showing a diverse range of possible optimal solutions potentially representing different priorities (see Fig. 5b, c and f).

In addition, minimising f_{flood} conflicted with minimising f_{heat} and f_{dist}. The conflict with f_{heat} occurs as low density areas coincide with flood risk areas in the north of the study area, whilst the conflict with f_{dist} occurs against due to the presence of several flood zones in close proximity to the CBD. The conflict between f_{flood} and f_{sprawl} is minor as there are many areas within the urban extent which are away from flood zone areas. The periodicity apparent in Fig. 5a, d and e is because flood risk is parameterised in three discrete values: 1 in 100 floodplain, 1 in 1000 year floodplain and areas of no flood risk. The trade-off curve that emerges from the optimisation allows a planner to explore the costs of improving a particular objective. Table 1 compares the extremes of these trade-offs, for example achieving $\min\ (f_{heat}) \in S_b$ leads to normalised performance in f_{flood} of 0.46.

Interestingly, as shown in Fig. 5 and Table 1, solutions that are optimal for more than one objective seem to generally perform reasonably well against others. This is especially true in the trade-off curve between f_{heat} vs f_{dist} and f_{heat} vs f_{sprawl} with 23 and 12 Pareto-optimal solutions on their Pareto fronts respectively. For example a spatial configuration is found which manages to achieve relatively good normalised values of 0.27 and 0.2 for f_{heat} and f_{dist} respectively. Thus, planners selecting any Pareto-optimal solution would be close to the best trade-off in terms of many other objectives. Although the spread is greater for f_{heat} vs f_{dist} the majority of these multi-objective Pareto-optimal solutions outperform the councils' own development plan.

Table 2
Performance of the best un-weighted Pareto-optimal result against Middlesbrough Council's development plan.

	Middlesbrough Development Plan	Best un-weighted Pareto-optimal spatial plan (Fig. 3b)	% improvement	% solutions found outperform plan for objective
f_{flood}	88.0	96	0	0
f_{heat}	3991.8	3777.4	6	85
f_{dist}	4679.3	3407.8	37	68
f_{sprawl}	29.6	13.0	230	88
Green space	24	0	Na	100

3.2. Multi-objective Pareto-optimal solutions

Fig. 6 shows the spatial development strategy of the best performing configurations for each individual sustainability objective in the Pareto-optimal set, whilst Table 1 shows the performance of each configuration against the other sustainability objectives. In order to achieve the best performance in f_{heat} the spatial configuration for $\min\ (f_{heat}) \in S_b$ (Fig. 6a) is achieved at the expense of locating development outside the urban extent (negatively affecting f_{sprawl}) and within flood zones in the north of the study area. Moreover, many optimal solutions have development sites in the southeast of the study area which significantly worsens the performance of the configuration in f_{dist} (normalised performance of 0.59).

The spatial configuration for $\min\ (f_{flood}) \in S_b$ (Fig. 6b) avoids all floodplain development (i.e. $f_{flood} = 0$), and although this configuration also performs well against f_{sprawl}, it does not perform particularly well against f_{dist} and f_{heat} (0.66 and 0.41 respectively).

As noted earlier, there is a conflict present between f_{dist} and f_{sprawl} and optimising either one of these objectives comes at the expense of an increase in f_{heat}. Therefore $\min\ (f_{dist}) \in S_b$ and $\min\ (f_{sprawl}) \in S_b$ achieve performances in f_{heat} of 0.63 and 0.49 respectively (Table 1). However, $\min\ (f_{dist}) \in S_b$ performs much worse against f_{flood} than $\min\ (f_{dist}) \in S_b$ as the latter spatially assigns sites to areas within flood zones near the CBD.

3.3. Performance of Pareto-optimal sets

Fig. 7 shows the parallel line plot of the median solution for the possible pairwise combination of objectives and MOPO solutions. This provides a visual overview of the pattern of their relative performances. It demonstrates already known relations as the median for the solution $\min\ (f_{heat}, f_{flood}) \in S_b$ performs inferiorly against f_{dist} and f_{sprawl}, reflecting the conflict between risk management sustainability objectives and those objectives seeking to mitigate carbon emissions. Similarly, the median solution for $\min\ (f_{sprawl}, f_{heat}) \in S_b$ has an adverse performance against f_{heat} and f_{flood}. However interestingly the median solution for $\min\ (f_{flood}, f_{sprawl}) \in S_b$ performs much better in f_{dist} than f_{heat} suggesting they have an element of corresponding with the former and can be optimised simultaneously. Plotting additional solutions in this way would provide an overview of how well they perform across all four objectives.

Fig. 8 shows a parallel line plot demonstrating the range of multi-objective Pareto-optimal solutions across the four sustainability objectives along with the best un-weighted Pareto-optimal solution (presented in Fig. 4b). The figure demonstrates that the best un-weighted Pareto-optimal solution performs relatively well across all four objectives. However on close inspection it is outperformed in at least one objective by all of the other multi-objective Pareto-optimal solutions. The range of multi-objective Pareto-optimal solutions shows the range of final solutions which planners can choose from, taking in their own priorities whilst assured in relatively good performances in non-prioritised objectives.

3.4. Ranked Pareto-optimal development locations

Fig. 9 presents the ranked Pareto-optimal locations of sites designated by the MOPO solutions highlighting locales in the study area which are more suitable for the location of development. Spatially, the results demonstrate particular patterns of development which are optimal for the objectives outlined. Areas consistently spatially assigned by the MOPO solutions include the north and northwest of the study area due to the proximity of the CBD and heat hazard being smaller in the northwest. Moreover there is a consistent assignment of sites in areas

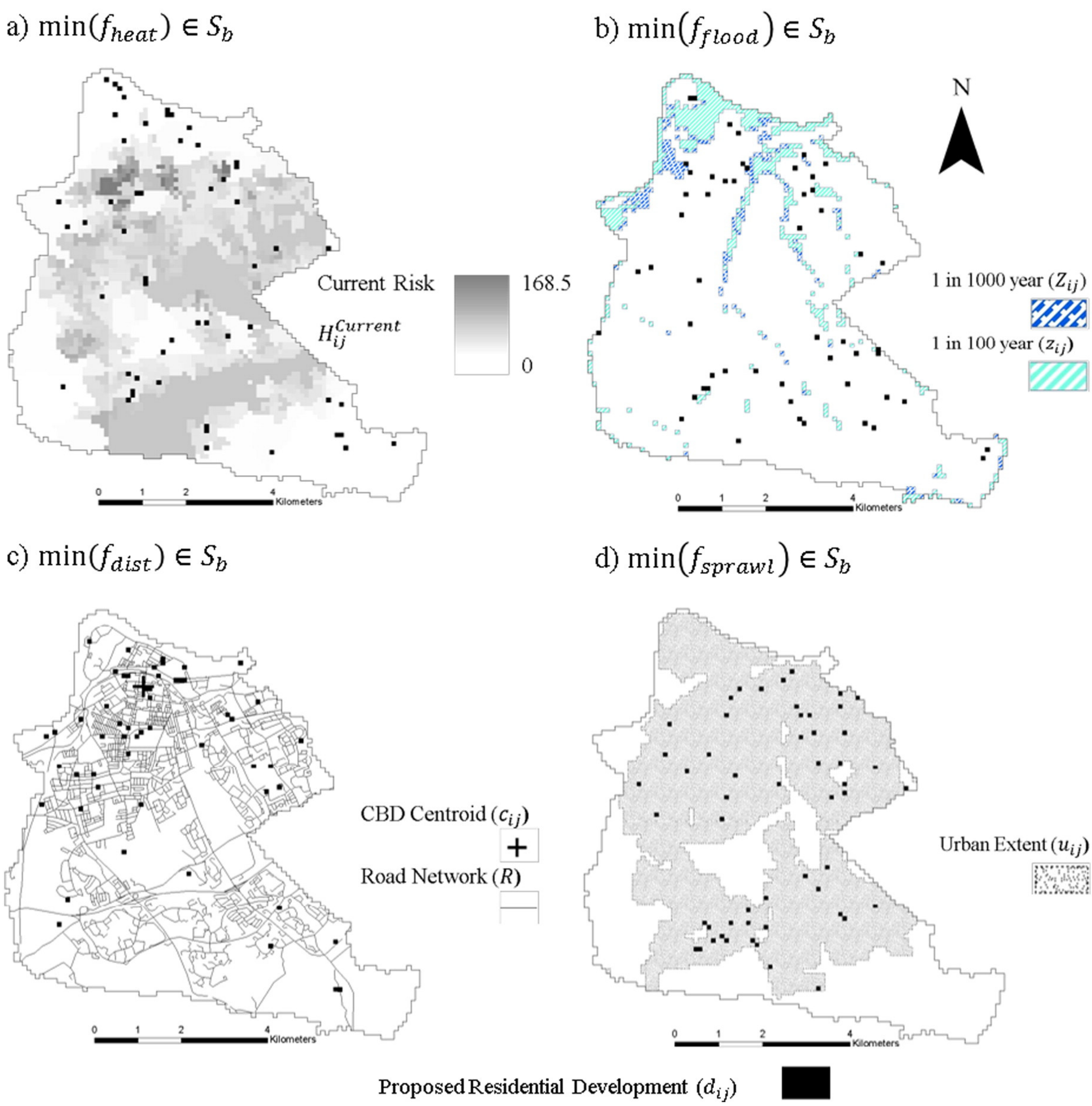

Fig. 6. Best performing Pareto-optimal spatial configurations for objective function a) f_{heat}; b) f_{flood}; c) f_{dist}; and d) f_{sprawl}.

of the southeast and south central of the study area which are within the urban extent whilst retaining a lower than average heat risk. The areas with the highest rank are within the upmost north of study area as well as central north.

4. Conclusions

Currently, there is a need to redesign cities in order to increase their resilience to climate induced hazards, whilst mitigating greenhouse gas

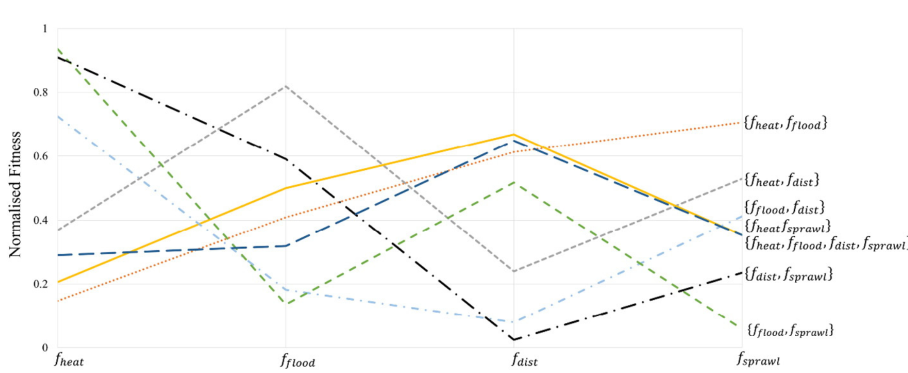

Fig. 7. Parallel line plots of the normalised objective score of the median solution for all the Pareto-optimal sets in the four objectives (tri-objective solutions are not shown for clarity).

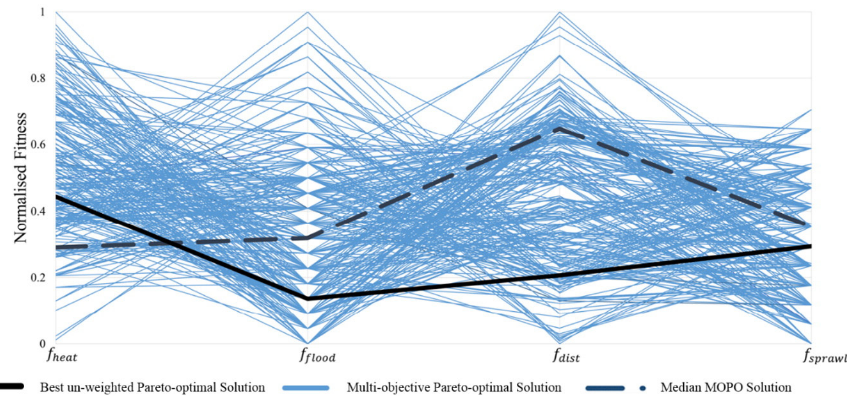

Fig. 8. Parallel line plots of the normalised objective score of the MOPO solutions ($\boldsymbol{F} = \{\boldsymbol{f_{heat}}, \boldsymbol{f_{flood}}, \boldsymbol{f_{dist}}, \boldsymbol{f_{sprawl}}\}$) against the best performing un-weighted Pareto-optimal solution (presented in Fig. 4b).

emissions. However during this process there needs to be oversight to ensure that conflicts do not occur between sustainability objectives, or where they are unavoidable, that their spatial impact is minimised. To this end, this paper has demonstrated that spatial optimisation has the potential to provide planners with detailed information on spatial development patterns that are optimal to one or more objectives, whilst understanding their sensitivities to other potentially conflicting long-term sustainability objectives. This analysis, and the diagnostic information contained within the full set of results, provides an evidence basis to assist planners and decision makers to better meet sustainability objectives and achieve broader sustainable patterns of development. The application of the spatial optimisation framework demonstrates for the real-world case study the ability to recognise potential development patterns that are potentially more sustainable than the planned situation. The framework achieves this improvement in performance through considering a wide possible range of solutions before converging towards most optimal spatial configurations. The results explore Pareto-optimal spatial configurations which demonstrate that the best-trade-offs achievable between separate sustainability objectives before a series of robust spatial development plans that are Pareto-optimal throughout the entire series of objectives are found. Each of these Pareto-optimal spatial development plans is better than all the development plans found by the optimisation algorithm in at least one of the sustainability objectives outlined.

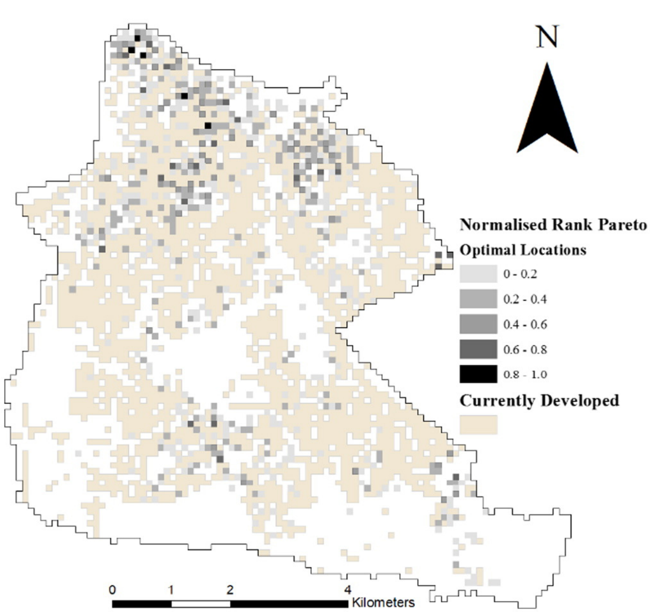

Fig. 9. Spatial frequency of site assignment based on the MOPO solution.

Resulting development plans significantly outperform the current development trend as set out by the local authority. The use of the Pareto-optimal approach provides a rich set of diagnostic information on the possible trade-offs, with the potential to constitute a spatial decision support tool. These optimal spatial plans identify a sub-set of possible planning objectives that, if considered with other qualitative planning objectives, can be used to inform final panning decisions. A major strength of this approach is the ability to present assessments of each objective alongside the resulting spatial pattern of development. Extraction of non-dominated Pareto-optimal spatial configurations between pairs of sustainability objectives provides planners with a clear quantitative and visual characterisation of the potential conflicts present between the sustainability objectives investigated. The results of the Pareto-optimisation over the entire set of objectives provide the spatial configurations which have the best possible trade-offs across all objectives, providing planners with a number of best case development strategies for the criteria investigated.

It has long been recognised (e.g., Tinbergen, 1956) that there are both political and analytical aspects to decision making. This work contributes to the latter supporting the use of urban modelling to support spatial planning. To this end, although this paper has presented a framework that spatially optimises development for a set of 4 sustainability objectives it has the flexibility to incorporate further sustainability objectives within such analysis, such as those relating to transport policy and quality of life. Moreover, result-sets are not intended to be a 'final product' but rather act as an evidence base upon which further qualitative and quantitative analyses can be applied to develop a final development plan. This could take the form of multi-criteria decision making techniques such as weighting or sensitivity analysis on the results. Although the literature notes that planners are positive to the use of such modelling tools (Keirstead & Shah, 2013) the high dimensionality of the results presented here would benefit from a user interface in order to facilitate exploration of the results and sustainability trade-offs. However the work provides valuable knowledge to planners by pointing towards trends of development optimum in the sense of minimising sustainability conflicts.

Interest in the role of spatial optimisation can play within urban system research and spatial planning in particular has resulted, as noted, in a wide range of multi-objective optimisation approaches being investigated. In this context, there is a need within the spatial optimisation community to provide benchmark comparisons of the relative strengths and weaknesses of these different approaches for particular applied problems. In the context of spatial multi-objective urban sustainability analysis. The framework developed in this paper offers a flexible means by which such an appraisal could be undertaken.

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Appendix A

Table A
Notation glossary.

Notation	Description
i,j	Location on grid
d_{ij}	Location of a site designated for development with respect to location on grid
D	A collection of development sites where $d_{ij} \in D$
f_{heat}	Objective function representing heat risk
f_{flood}	Objective function representing flood risk
f_{dist}	Objective function representing the average distance of development to CBD
f_{sprawl}	Objective function representing urban sprawl
Parameterisation	
h_{ij}	Heatwave hazard annual frequency raster
v_{ij}	Population vulnerability raster
H_{ij}^{Future}	Future heat risk raster; product of h_{ij} and updated v_{ij}
$H_{ij}^{Current}$	Current heat risk raster; product of h_{ij} and v_{ij}
Z_{ij}	Cells within 1 in 1000 flood zones
z_{ij}	Cells within 1 in 100 flood zones
c_{ij}	CBD centroid
R	Road network
P	Shortest path along the road network
u_{ij}	Cells designated as within the current urban extent
g_{ij}	Cells designated as greenspace
SA Algorithm	
S_b	List of solutions found by the SA algorithm
s	Solution within S_b
n	Iterations within entire SA algorithm procedure
m	Iterations of the application of the SA algorithm
f_n	Objective functions of a solution at the nth iteration
f_b	Best objective function found throughout the simulated annealing operion
D_n	Spatial configuration of the solution at the nth iteration
D_b	Best performing spatial configuration found throughout the simulated annealing operation
Δ	Magnitude of difference between $f_n$and f_{n+1}
T	Temperature variable used by the simulated annealing procedure
C	Cooling factor applied to temperature variable T
T_{end}	Ending parameter for T which terminates the algorithm
$\mathbb{R}$	Real number between 0 and 1
f	An element of F
F	Set of objective functions
p	Non-dominated solution within the non-dominated list
N	Non-dominated list

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